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Default Risk Prediction for Small and Micro Enterprises Using a Wide and Deep Learning Framework

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Abstract: Delinquency risk prediction is a core component of credit loan operations, directly impacting the profitability of lending institutions and the control of bad debt. With the rapid development of mobile internet, credit services have become widely accessible to the general public. Traditional risk control methods based on manual rule-making are gradually being replaced by data-driven intelligent modeling techniques. Existing approaches mainly include traditional machine learning models and deep learning models. The former offers strong interpretability but limited predictive performance, while the latter excels in prediction accuracy but suffers from weak interpretability and a high risk of overfitting. To balance the strengths of both, this paper draws inspiration from the Wide & Deep model architecture commonly used in recommendation systems and proposes a hybrid modeling framework that combines logistic regression with deep neural networks. This framework is designed to extract key features from both structured and unstructured data and to predict the probability of delinquency through a unified linear layer. Specifically, the wide component utilizes logistic regression to process structured variables such as basic enterprise information and cross features, while the deep component employs a three-layer fully connected neural network to handle unstructured data such as transaction flows. Through end-to-end training, the model simultaneously optimizes both components, thereby enhancing overall performance. Experiments conducted on a real-world credit dataset for small and micro enterprises demonstrate that the proposed model outperforms traditional baseline models across multiple evaluation metrics, including AUC, Precision, Recall, and F1-score, confirming the effectiveness and practical value of the approach in delinquency risk prediction. This research not only improves the predictive accuracy of risk control models but also offers new insights into modeling complex and heterogeneous credit data.

Keywords: Small and Micro Enterprises, Wide and Deep Learning, Credit Scoring, Machine Learning, Deep Neural Networks

1. Introduction

In recent years, with the deep implementation of the "Internet Plus" strategy and the continuous improvement of mobile financial infrastructure, credit services have rapidly penetrated into the daily lives of individuals and small and micro enterprises (SMEs). Mobile-based services such as digital lending, payments, credit evaluation, and risk management have developed at an unprecedented pace, significantly improving the accessibility and convenience of financial services. At the same time, they have also increased the complexity and heterogeneity of customer profiles and risk distributions in the credit market.

Particularly for micro-loan and fast-approval products, traditional rule-based risk control approaches are no longer sufficient to meet the demands of high-frequency, high-concurrency business environments. As a result, there is an urgent need for more automated and intelligent risk modeling systems to enable accurate assessment and dynamic identification of delinquency risks.

Among the many components of credit risk management, predicting the probability of loan delinquency is one of the most critical tasks. It directly affects default rate control, capital allocation efficiency, and the balance between risk and return for financial institutions. With the advancement of data mining and artificial intelligence, the industry has gradually shifted from qualitative assessments based on rules and expert experience to quantitative modeling methods driven by massive amounts of user data. Machine learning and deep learning techniques have emerged as dominant modeling tools and have achieved remarkable results in various financial risk control scenarios.

Traditional machine learning models, such as logistic regression, support vector machines (SVM), decision trees, and their ensemble variants (e.g., GBDT and XGBoost), rely primarily on structured input data and offer strong interpretability and stability. These models are especially favored in highly regulated financial environments. However, they are limited in their ability to capture complex nonlinear relationships and often struggle to extract deep patterns from unstructured data sources, such as behavioral sequences, text information, or transaction flows. In contrast, deep learning models—including feedforward neural networks (FNN/BP), convolutional neural networks (CNN), and long short-term memory (LSTM) networks—can automatically learn high-level features through end-to-end training. With powerful representational and generalization abilities, they have achieved widespread success in fields such as image recognition and natural language processing and are increasingly being adopted in credit modeling tasks. Nevertheless, the complexity, limited interpretability, and high risk of overfitting in deep models pose challenges for their large-scale deployment in financial applications.

To overcome these limitations, recent research has focused on hybrid modeling approaches that combine the interpretability of traditional models with the representational power of deep learning. One notable example is the Wide & Deep Learning framework proposed by Google, which integrates shallow linear models with deep neural networks. By learning from both structured and unstructured features in parallel, the framework achieves a balance between memorization and generalization, significantly improving overall model performance in recommendation systems. This architecture has since been successfully adapted to a variety of domains, including power grid anomaly detection, scientific text classification, and medical diagnostics , demonstrating strong applicability and scalability.

To this end, this study proposes a Wide & Deep-based delinquency risk prediction model tailored to the SME lending context. The model employs logistic regression to process structured information (such as industry category, location, and real-name verification status) and a multi-layer perceptron (MLP) to learn representations from unstructured transactional data. A feature fusion layer is designed to jointly optimize both inputs, enabling end-to-end training and enhancing the model's predictive performance, interpretability, and robustness. Empirical experiments on a real-world SME lending dataset show that the proposed model outperforms existing baseline models across multiple evaluation metrics, underscoring its practical value.

In summary, this study not only offers a feasible and effective modeling approach for SME credit risk management but also contributes empirical evidence supporting the broader application of Wide & Deep Learning architectures in financial domains.

2. Related Work

With the rapid development of financial technology, credit risk prediction models have evolved from traditional rule-based systems to data-driven approaches combining machine learning and deep learning. To improve predictive accuracy while maintaining interpretability, researchers have increasingly adopted hybrid frameworks that integrate traditional models with deep neural networks.

To begin with, Kai et al. [1] proposed an efficient compression strategy for large-scale language models via distillation and fine-tuning, offering a basis for building lightweight, high-performance deep models. Wang [2] addressed data imbalance in credit card fraud detection using ensemble learning combined with resampling techniques, significantly improving performance metrics. Wang et al. [3] explored generative diffusion models for user interface design—though primarily in human-computer interaction, their generative learning methodology holds relevance for model structuring in financial domains.

Lou et al. [4] integrated probabilistic graphical models with variational inference to handle class imbalance, while Liang et al. [5] introduced contrastive and self-supervised learning approaches to improve representations from complex data—both methods contribute to robust feature learning in finance. Bao et al. [6] applied deep anomaly detection techniques to high-frequency trading data, demonstrating real-world applicability in volatile environments.

In fraud detection, Wang [7] utilized hierarchical multi-source data fusion with dropout regularization, and Wang [8] proposed adaptive Markov network classification to enhance model performance under imbalanced settings. Liu [9] developed multimodal factor models to improve stock market prediction through cross-domain data integration.

Deep learning architectures like CNNs, BiLSTMs, and Transformers have also gained traction. Du [10] presented EfficiencyNet, combining separable convolution and self-attention for audit fraud detection. Wang [11] employed bidirectional Transformers for premium risk prediction, highlighting their sequential modeling strength, while Feng [12] constructed a BiLSTM-Transformer hybrid to detect anomalies in financial transaction streams.

Zhou et al. [13] applied temporal convolutional networks (TCNs) to blockchain HFT signal prediction, extending traditional forecasting techniques. Wu et al. [14] introduced adaptive feature interaction models for credit risk prediction in digital finance. Liu [15] enhanced CNN structures to improve stock volatility forecasting performance.

For textual and unstructured data, Du [16] applied 1D-CNNs for financial text classification, while Yao [17] improved Transformer models for temporal and multi-dimensional dependencies in stock prediction. Cheng et al. [18] integrated CNN and BiLSTM into a framework for systemic financial risk modeling.

Du et al. [19] proposed a structured reasoning framework leveraging probabilistic models to handle data imbalance. Wang et al. [20] conducted a comparative study of credit default models, offering interpretability insights crucial for financial deployments.

Although some studies focus on human-computer interaction, such as Sun's [21] fuzzy logic-based visual communication optimization and Duan's [22] knowledge graph-enhanced sentiment systems, they offer methodological inspiration for intelligent system design. Wu et al. [23] combined CNN and GRU for financial sentiment analysis, contributing to smart alert systems.

Together, these studies form a foundation that spans preprocessing, model training, deep learning, interpretability, and deployment. The proposed Wide & Deep hybrid model builds on these contributions to offer a more robust and interpretable solution for SME credit risk prediction.

3. Wide and Deep Model for Credit Risk Prediction

To effectively predict the delinquency risk of loans issued to small and micro enterprises (SMEs), this study proposes a hybrid modeling approach based on the Wide & Deep architecture. The proposed framework leverages the strengths of both traditional machine learning and deep learning, enabling simultaneous processing of structured and unstructured features through an end-to-end training strategy. This design enhances both predictive performance and generalization capabilities.

The dataset used in this research was obtained through a collaboration with a third-party payment service provider, which offered partial access to SME transaction flow data and complete records of their loan applications to partner financial institutions. While the model is tailored for SME credit risk prediction, it exhibits strong generalizability and can be extended to other lending scenarios such as personal loans and corporate credit evaluation. Figure 1 illustrates the overall architecture of the Wide and Deep model proposed in this study

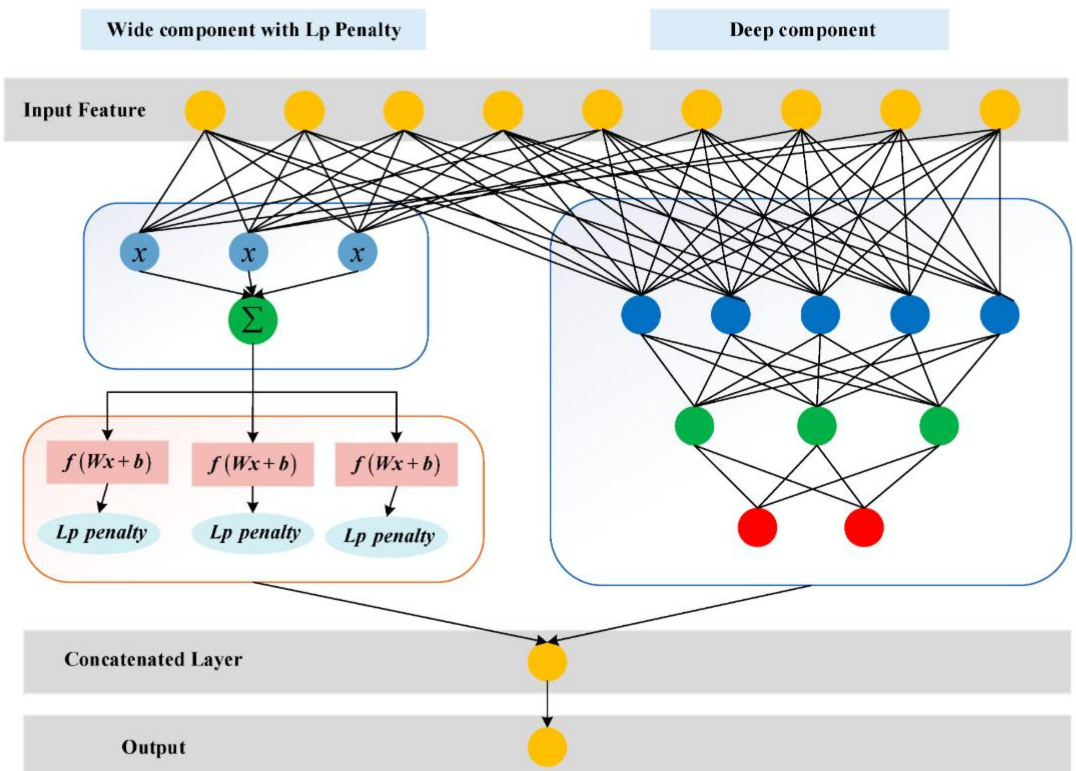

Figure 1. Wide and Deep Model for Credit Risk Prediction

3.1 Wide Component

The wide component adopts a traditional logistic regression model and focuses on processing high-dimensional structured features. The inputs include fundamental attributes of SMEs such as industry type, registration city, gender of the legal representative, and real-name authentication status. Additionally, a set of cross features is constructed to explicitly model interactions between variables.

All input features are encoded using one-hot encoding and represented as sparse vectors to ensure compatibility with linear models. The goal of feature crossing is to capture nonlinear interactions explicitly while maintaining model interpretability. Due to its simplicity, efficiency, and ease of audit, logistic regression remains a widely adopted modeling approach in the financial sector.

3.2 Deep Component

The deep component is constructed using a multi-layer perceptron (MLP) and is responsible for extracting high-level semantic features from unstructured data such as transaction records. The input includes behavioral metrics like the total number of historical transactions, total transaction amount, transaction amount variance, and average daily transaction frequency. These indicators comprehensively reflect business activity levels and financial health, providing important signals for assessing an enterprise's short-term solvency and cash flow status.

The deep network consists of three fully connected layers with 256, 128, and 64 neurons, respectively. Each layer uses the Rectified Linear Unit (ReLU) as the activation function:

$$\mathbf{X}_{t+1} = \mathrm{ReLU}(\mathbf{W}_t \mathbf{X}_t + \mathbf{b}_t)$$

where W_t is the weight matrix of the t layer, X_t is the input from the previous layer, and b_t is the bias term. The nonlinearity of ReLU helps the model capture complex behavioral patterns while mitigating the vanishing gradient problem during training.

3.3 Feature Fusion and Output Prediction

In the fusion phase, the sparse vector output X_{wide} from the wide component is concatenated with the dense output X_{deep} from the deep component to form a unified feature representation. This fused vector is then passed through a linear output layer followed by a sigmoid activation function to predict the probability of delinquency:

$$y = \sigma(\mathbf{W}_{\text{wide}} \mathbf{X}_{\text{wide}} + \mathbf{W}_{\text{deep}} \mathbf{X}_{\text{deep}} + b)$$

Here, $\sigma(\cdot)$ denotes the sigmoid function, and the output $y \in (0,1)$ represents the predicted probability of a loan default or delinquency.

To optimize the model during training, binary cross-entropy is used as the loss function:

$$\mathcal{L} = -\sum_{i=1}^{N} [y_i \log \hat{y}_i + (1 - y_i) \log(1 - \hat{y}_i)]$$

3.4 Advantages and Application Value

The proposed Wide & Deep architecture offers the following advantages:

Complementary structure: The logistic regression component provides interpretability and stability, while the deep neural network offers strong feature learning capabilities.End-to-end optimization: Joint training via a unified loss function eliminates the need for manual integration and reduces system complexity.Multi-source adaptability: The architecture is extensible to incorporate other heterogeneous data types such as graph-based inputs, textual descriptions, or image data.Overall, the proposed Wide & Deep model serves as an effective bridge between theoretical design and practical business needs. It offers a smart, auditable, and high-performing risk control solution that can be readily applied to financial scenarios requiring the integration of diverse data sources.

4. Experimental Evaluation

To validate the effectiveness of the proposed Wide and Deep model for predicting the default risk of small and micro enterprises (SMEs), we conducted comprehensive empirical experiments using real-world business data. The evaluation includes data description, experimental setup, performance comparison, and sensitivity analysis. The model's effectiveness is assessed from both predictive accuracy and robustness perspectives.

4.1 Data Description

The dataset used in this study was obtained from a partner payment platform and consists of loan records, business transaction logs, and enterprise profile information for a subset of SMEs. We selected enterprises whose loan outcomes are clearly defined, including:

Non-default samples (label = 0): Loans that were fully repaid on time.

Default samples (label = 1): Either loans overdue by more than 30 days or loan applications that were rejected due to the borrower’s negative credit history.

After filtering, the positive-to-negative sample ratio was approximately 6:4, which is suitable for binary classification modeling. The final dataset contains 129,880 valid samples, randomly split into training, validation, and test sets in a ratio of 60%, 20%, and 20%, respectively.

Four main types of features were used as model inputs:

1.Basic enterprise information: Including legal representative gender, primary and secondary industry classification, city of registration, real-name verification status, and bank account validation.

2. Cross features: Engineered by combining categorical variables, such as "city × industry" or "gender × verification status", to model feature interactions.

3. Historical credit behavior: Including past loan frequency, average days overdue, and previous delinquency counts, indicating the enterprise’s historical creditworthiness.

4. Transaction log features: Aggregated statistics such as total transaction amount, number of transactions, daily average, and variance measures, reflecting the firm’s operational and financial health.

5. Structured features (types 1–3) were input into the wide component, while behavioral features (type 4) were fed into the deep component.

4.2 Experimental Setup

The wide component employed logistic regression with cross features, and the deep component utilized a three-layer fully connected neural network, consistent with the architecture described in Section 3. For benchmarking, we implemented five baseline models:

Logistic Regression

Deep Neural Network (DNN)
Wide & Deep (without cross features)

Logistic Regression + Cross Features
DNN + Cross Features
Wide & Deep + Cross Features (our proposed model)

4.2.1 Hyperparameter Settings

We optimized hyperparameters on the validation set to ensure the best performance on the test set. The final configuration is listed in Table 1.

Table 1: Hyperparameter Settings

Parameter	**Description**	**Optimal Value**
batch_size	Batch size	256
learning_rate	Learning rate	0.0001
loss	Loss function	Binary cross-entropy
optimizer	Optimization algorithm	Adam
activation	Activation function	ReLU

4.2.2 Evaluation Metrics

We adopted four widely used classification metrics to comprehensively evaluate model performance:

Precision: The proportion of predicted positives that are actually positive.

Recall: The proportion of actual positives correctly identified by the model.

F1-Score: The harmonic mean of precision and recall, balancing both metrics.

AUC (Area Under the Curve): Measures the model's ability to distinguish between classes.

Higher values in all four metrics indicate better performance.

4.3 Results and Analysis

Table 2: presents the evaluation results of the proposed model and baseline methods on the test set.

Model Type	**AUC**	**Precision**	**Recall**	**F1-Score**
Logistic Regression	0.6509	0.6526	0.6849	0.6203
DNN	0.6529	0.6561	0.6871	0.6337
Wide & Deep	0.6616	0.6679	0.6933	0.6377
Logistic Regression + Cross	0.6508	0.6507	0.6841	0.6196
DNN + Cross	0.6607	0.6638	0.6911	0.6495
Wide & Deep + Cross (Ours)	**0.669**	**0.669**	**0.695**	**0.653**

The proposed Wide & Deep model with cross features consistently outperforms all baseline methods across all metrics, demonstrating its superior capability in capturing both linear and nonlinear feature interactions. Notably, it achieves the highest AUC and F1-score, indicating enhanced classification performance and robustness.

4.4 Sensitivity Analysis

To assess the model's robustness under different training configurations, we conducted sensitivity analysis on three key hyperparameters: the number of training epochs, batch size, and learning rate. The AUC and F1-score results are plotted in Figure 2.

In summary, the proposed model demonstrates strong predictive power, stable convergence behavior, and low sensitivity to hyperparameter variation, making it well-suited for practical deployment in risk control systems.

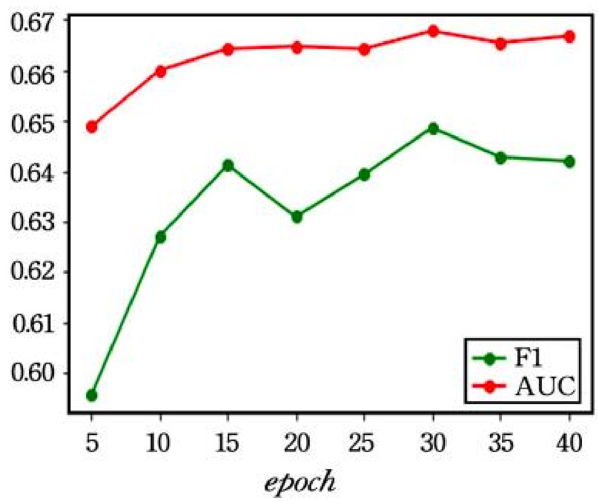

Figure 2(a): Both AUC and F1-score converge at around 30–35 epochs, with a slight decline afterwards, indicating potential overfitting.

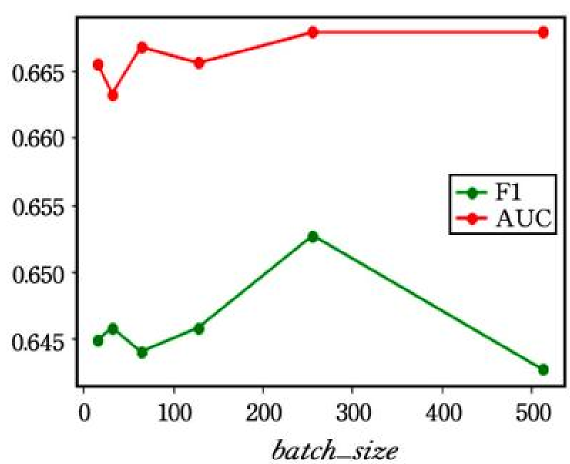

Figure 2(b): Batch size values from 128 to 256 yield the most stable results; too small a batch size leads to performance fluctuations.

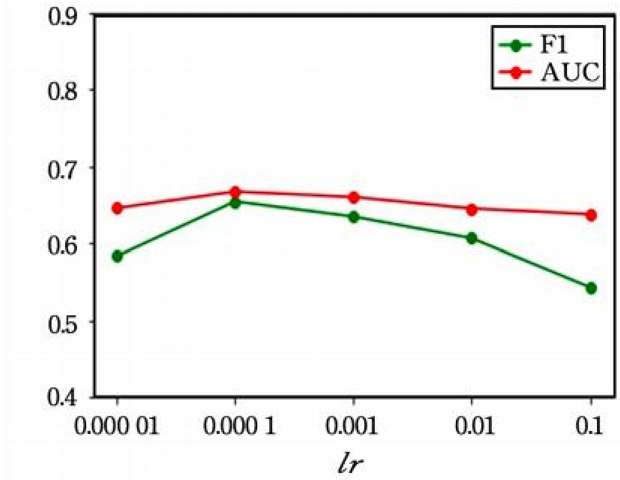

Figure 2(c): A learning rate of 0.0001 provides optimal performance, while larger values degrade results, confirming the model benefits from gradual convergence.

5. Conclusion and Future Work

This paper proposed a credit risk prediction framework for small and micro enterprises based on the Wide and Deep learning architecture. The model combines the strengths of traditional logistic regression and deep neural networks to jointly model structured and unstructured data. Specifically, the wide component captures high-dimensional cross features from structured inputs, while the deep component extracts high-level representations from unstructured transaction sequences. These two components are integrated via a unified fully connected layer, enabling end-to-end optimization and improved prediction accuracy.

Experimental results on a real-world dataset demonstrated that the proposed model outperforms several classical baselines—including logistic regression, deep neural networks, and their variants with cross features—in terms of AUC, precision, recall, and F1-score. The sensitivity analysis further validated the model's convergence speed and robustness under different hyperparameter configurations. Overall, the model exhibits both strong predictive performance and practical applicability, providing an effective solution for delinquency risk identification in digital lending scenarios.

In future work, we plan to enhance the model in the following directions:

Model Extension: Replace the wide component with tree-based models such as GBDT or XGBoost to improve the handling of categorical feature interactions while maintaining interpretability.Deep Component Optimization: Introduce recurrent neural networks (e.g., LSTM, GRU) or temporal convolutional networks (TCN) to more effectively capture sequential patterns in transaction logs. Attention mechanisms may also be incorporated to identify salient features.Feature Fusion Strategies: Explore more sophisticated fusion techniques—such as gating mechanisms or attention-based cross layers—to improve the interaction modeling between wide and deep representations.Broader Applications: Generalize the current framework to other risk control tasks, such as personal loan default prediction, credit scoring, or fraud detection, thereby extending its utility in financial technology applications.Through continued refinement and expansion, the proposed wide and deep learning framework is expected to contribute to more intelligent, adaptive, and trustworthy risk control systems in the evolving digital finance landscape.

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